NORTHWEST NAZARENE UNIVERSITY

Prediction of Fruit Yield Using Blossom Counting App

THESIS
Submitted to the Department of Mathematics and Computer Science
in partial fulfillment of the requirements
for the degree of
BACHELOR OF SCIENCE (or ARTS)

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ABSTRACT

Prediction of Fruit Yield using Blossom Counting App
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Idaho farmers face the challenge of hiring manual laborers during the harvesting season due to the shortage of workers. This challenge creates financial problems, one of which is that many unharvested fruits are left in the orchards at the end of the agricultural season. Predicting fruit yield count early in the season allows farmers to have a general idea of how many manual laborers to acquire before harvesting. The use of a mobile application with integrated image processing tools can assist in predicting fruit yield before harvest. This project developed a farmer-friendly app for mobile devices to count blossoms on apple trees. Results from field evaluation demonstrate a positive correlation between the number of blossoms detected and the final fruit count. The following method of predicting fruit yield count displays a promising approach with time efficiency and simplicity.

Acknowledgement

My whole academic journey has had its ups and downs, for which I am very thankful. To begin my acknowledgment, I would like to thank my Lord and Savior, Jesus Christ, for he has blessed me with so many gifts. The position I am in today would not be possible if it weren't for the sacrifices and hard work my parents have put in. I cannot express my gratitude enough for leaving their country and traveling to foreign lands to seek better opportunities for my brother and me.

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Introduction

One of the issues we face in today's society is a growing population. With the rise of the population, it will result in the demand for food to increase. The increased food demands force farmers who produce and distribute these products to find ways to increase production. Farmers must be able to adapt to these changes and adapt fast. A key idea that will play a vital role in the future success of farming is the idea of integrating technology into farms.

The increased demand for food creates multiple challenges that will arise in the future. Some of the challenges that stem from the issue are increasing total laborers working on farms, risking the quality of crops, a rise in global market price, and environmental changes (Zhang, Pierce, 2016). In a world where efficiency is a crucial necessity, it is essential to explore methods of achieving efficiency in all aspects of agricultural production. Adopting the use of technology within agriculture will play a vital role in the future success of agricultural production.

Idaho farmers are tasked to meet the rapid increase in demands of food production and find enough manual laborers to harvest the crops within the orchards. The problem that farmers face is that there are not many willing to do the work, and, the occurrence of the pandemic added to the shortage of manual laborers. One solution to aid farmers in manual labor shortages depends on the H-2A Visa program hiring foreign citizens to do the jobs. However, farmers need to know in advance how many workers they need to hire. To know how much labor is needed, farmers need to estimate in advance how much crop will be produced. What the farmers do is, count the crops prior to the harvesting season to estimate how many workers it would require to harvest the crops. So, farmers need to be able to predict fruit yield count accurately. Some farming approaches to ensure accuracy in predicting fruit yield count are precision agriculture and integration of smart agriculture.

In this study, we are focusing on apple production. The current method for predicting the final fruit yield count for apples is counting the number of fruit drops within a small number of trees from the orchard. The next step is to take the value of the fruit count drop of the selected trees and apply it to the whole orchard. This method of predicting fruit yield count presents several flaws, such as it is time-consuming hand counting the fruits and the sample size is too small to represent the orchard. This project's proposed method is developing a farmer-friendly mobile application to count the number of blossoms, as it is widely assumed among local farmers that there is a positive correlation between blossoms and final fruit count.

The use of blossoms in predicting fruit count takes advantage of the changes of the apple tree throughout the season. Apple trees undergo significant changes throughout the year. They experience changes from seasonal progression and from external factors on farms. The changes that apple trees undergo through seasonal transitions are first, they produce blossoms or flowers as seen in Figure 1. As the agriculture season progresses, the blossoms turn into fruit drops (Figure 2), and towards the end of the season, they fully mature into the apples sold at local stores (Figure 3). The external factors that affect the fruits come from human interaction, animals picking fruits from trees, chemicals used on them, or simply the changing weather. For farmers, one of their responsibilities is to consider the changes that apples undergo and accurately predict fruit yield count. As discussed earlier, farmers need to predict fruit yield as this indicates how many workers to hire for the harvesting season. There have been several methods that have explored precision agriculture to predict fruit yield.


Figure 3 - Blossom


Figure 2 – Fruit Drops


Figure 1 – Matured Apple

Precision Agriculture is a method of orchard management that observes crops within farms to better understand the behavior of the orchard. One method of precision agriculture is the use of sensors to predict fruit yield using the canopy size of the tree (Zaman, Schumann, Hostler, 2006). An alternative method explores machine learning, mainly focusing on segmenting the fruits from the background for fruit yield estimation (Hung, Underwood, Nieto, Sukkarieh, 2015). Other studies include machine vision, mapping out the location of the fruits for better prediction of fruit yield (Swain, Zaman, Schumann, Percival, Bochtis, 2010). While these methods show promising results, they require many resources, time, and monitoring to be implemented within farms. This paper explores mobile devices as a potential primary tool for orchard management.

Individuals are heavily dependent upon smartphones due to their computing power and flexibility. Smartphones are flexible because they allow the development of customized applications. Almost all of the people including farmers use smartphones. Creating a smartphone app that has a farmer-centric architecture for orchard management could be useful for the farmers. The use of mobile applications to predict yield estimations has the potential to solve multiple issues. Unlike methods such as microsensors, machine learning, and machine vision, a smartphone in the fields does not require many resources, time, or monitoring. The goal of this study is to develop a farmer-friendly mobile application to count the number of blossoms on a tree.

Related Works

Traditional techniques that farmers have grown accustomed to producing food can no longer be heavily relied on, and instead, they should explore other means of orchard management. The work of Saik (2018) explores several areas that we can further study to improve orchard management.

Sensors

"Sensors would alert us to what kind of protective measures we could take to help the crop fight the disease before we would ever see the disease on the plant" (Saik, 2018). Sensors can detect crop diseases before it heavily affects the crop. Additionally, sensors can aid farmers in predicting fruit yield. One approach uses ultrasonically sensed tree size to monitor the size of the tree (Zaman, Schumann, Hostler, 2006). For this approach, the volume of the tree was used to determine the estimation of fruit yield. The use of sensors for precision agriculture also presents drawbacks. When using sensors, there are three things to consider:

1. Knowledge of the technical facet of micro-sensors.
2. Expense of implementation
3. Requires daily monitoring

These considerations do not meet the cost-benefits from the farmer's perspective. To meet these considerations takes a substantial amount of time and resources.

Machine Vision

A different approach to precision agriculture is Machine Vision. The concept of machine vision allows the user to enhance a system with the ability of sight. "Machine vision is a technology that provides a visual sensor to machine systems" (Bulanon et al., 2020). When using Machine vision, there are four facets to consider:

1. Scene Constraints
2. Image Acquisition
3. Image Processing
4. Actuation

Image constraints deal with the noise that the surrounding environments provide. Some image constraints come from the lighting of the sun and surrounding objects. Second, image acquisition is the medium decided in acquiring data. Mediums of acquisition are standard cameras, specialized cameras for a particular light spectrum, or video cameras. *Image processing* is the steps taken to remove or reduce the scene constraints to focus on the desired object. The last facet is actuation; this is where the course of action will be decided based on the information extracted from image processing. In this case, the farmer will know how much labor is needed for harvesting.

A study that uses the concept of machine vision is the estimation of wild blueberry (Swain, et al., 2010). For this study, the object that enhances a farm vehicle was a digital camera. The data captured by the camera is then passed to a computer to perform both calculating position and image processing. "The yield prediction method was based on the estimation of the blue pixels representing ripe fruit in the view of each image…" (Swain, Zaman, Schumann, Percival, Bochtis, 2010). The use of machine vision takes advantage of the farmer's motor vehicle to automate data acquisition. However, there are challenges when integrating machine vision within farms. The method of machine vision to predict yield estimation of wild blueberry required a camera and a computer to be mounted on a motor vehicle. The additional use of other technology makes this method complicated and intimidating because farmers are hesitant to use advanced technology.

Image Processing

The four facets of machine vision are equally important; however, for this project's scope, the fundamental concept that should be focused on within machine vision is image processing. The studies done by the Robotics Vision Lab at Northwest Nazarene University describe the process of developing a method that explores image processing (Bulanon et al., 2020). Within this work, the project's scope is to isolate peach blossoms from the background. For this study, the approach to predicting fruit yield is a correlation between blossoms detected by the algorithm to the final fruit count. This method's first step is to collect sample pixels of the following classes.

1. Sky
2. Blossoms
3. Leaves/Grass
4. Branches
5. Dirt

After collecting the pixel samples of the five classes, these pixels will then be plotted onto a chart. A linear function is applied to separate the blossom pixels from the other class pixels to isolate the blossom pixel as seen in Figure 4.

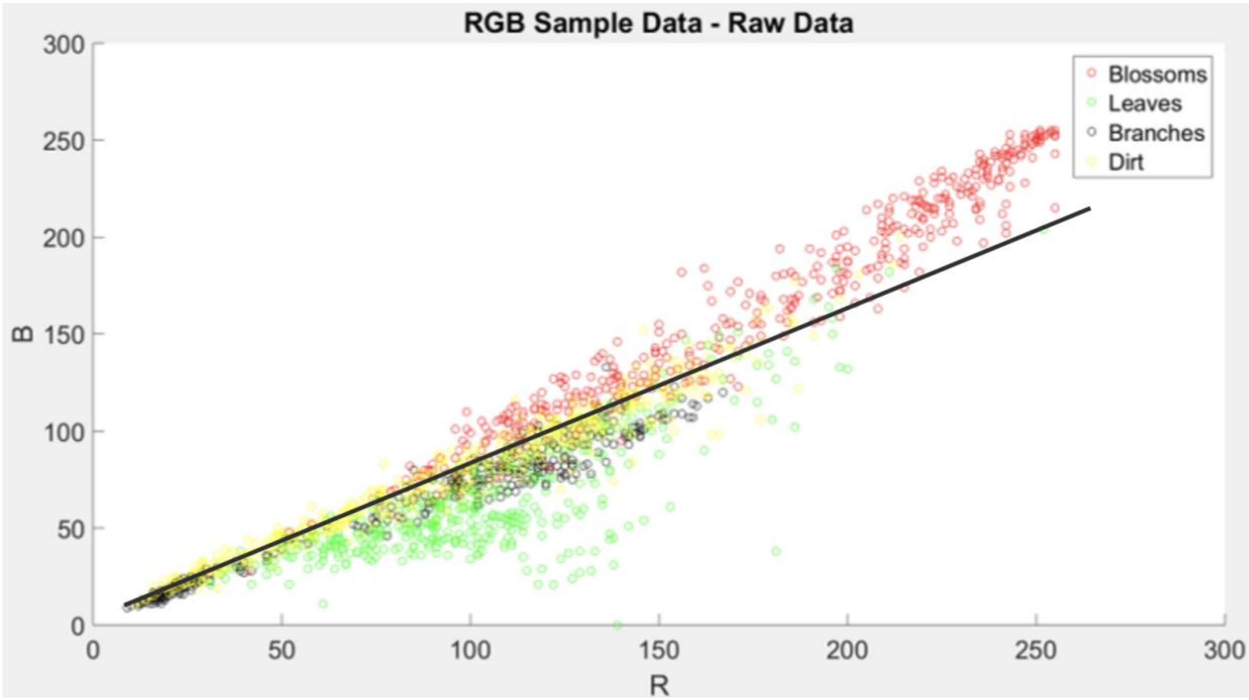

Figure 4 - Color Discriminant (Bulanon et al., 2020)

Figure 4 shows that the linear function represented by the black line separates the blossom pixels from the remaining classes. The line also represents the color discriminant function used to identify if the pixel is classified as a blossom pixel or not a blossom pixel. Figure 5 shows the flow of how the image is processed. First, the image is read through the program and then applies a color discriminant to isolate the blossoms. Once the blossoms have then been isolated, we then convert the result into a binary image to count the detected blossoms through blob analysis.

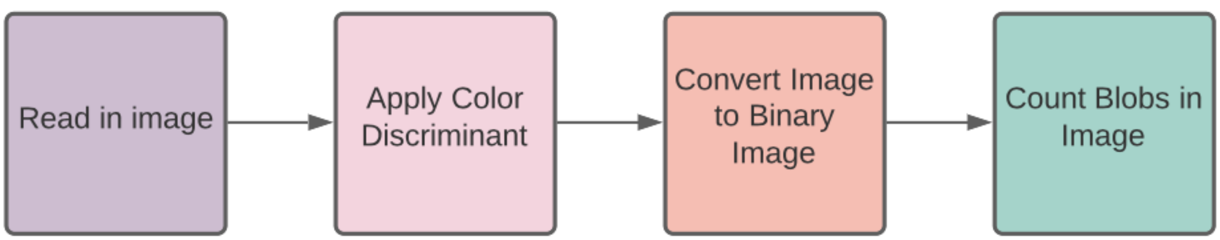

Figure 5 - Image Processing Flow Chart

Image processing as a tool for precision agriculture shows plenty of promise. Using and implementing image processing as the primary precision agriculture tool does have its setbacks. The challenges of applying image processing are the following:

1. This method used MATLAB for application development
2. Consistent filter for year-to-year application

MATLAB is a closed source integrated development environment. Deploying a program through MATLAB would cost money for farmers who wish to obtain this program. Using a color discriminant for the year-to-year use would not provide the ideal results. When considering the changes that crops undergo, external factors need to be applied but cannot be without substantial data. With limited accessibility to this tool and inconsistent results due to the unpredictability of crop behavior, image processing as a means of orchard management is not the ideal solution.

Machine Learning

Machine learning is a concept that has been heavily studied over recent years and has taken a giant stride. This method explores breaking down the learning process through different layers. As result, machine learning detects patterns that allow it to give a probabilistic interpretation and prediction for future patterns. The more layers a machine contains, the assumption can be made that it better understands the object or goal. Several ways that machine learning has been applied to agriculture are through image processing. An approach that uses image processing to implement machine learning includes predicting yield through counting blossoms (Bulanon et al., 2020). This study assumes a positive correlation between blossoms detected by the machine to fruit count.

This approach feeds in images that have been classified as blossoms to the machine. The classification method that was used through this method was manually placing bounding boxes around the blossom. These bounding boxes are the user's way of communicating to the machine, with 100% certainty that it is blossoming and nothing else. The duration of this study used 30 trees as its sample size, meaning there were 60 total full images to capture both sides of the tree.

The accuracy of the machine was tested by running a correlation of blossoms detected by the machine to the final fruit count. This method shows the potential of machine learning in predicting fruit yield by detecting blossoms within the image.

Machine learning with enough data, applied in agricultural uses displays a promising future, it also brings challenges of implementation such as:

1) Close Monitoring of Learning Process
2) Requires a lot of time
3) Requires Substantial Amount of Data

Developing a machine learning system to fit specific requirements takes a lot of time. There is gathering data, labeling data, choosing a model, training the model, and then testing the model. Through each phase, users are required to closely monitor the progress of the machine to ensure it meets the desired needs. To implement machine learning through agricultural uses requires both time and resources resulting in making this method of precision agriculture very complicated.

Mobile Application

The flexibility of a smartphone comes from the ability to create applications for several uses. With this in mind, an ongoing study to improve precision agriculture is E-Agriculture (Mendes, et al., 2020). The centralized idea behind "E-Agriculture" is connecting various devices to a reporting device and, in this case, a smartphone. With the recent advancements in technology, most fields have taken advantage of the concept of "Information and Communication Technology" (Smartphone Applications Targeting Precision Agriculture Practices—A Systematic Review). As farmers, it can be overwhelming to maintain an orchard, let alone improve the orchard for production using advanced technologies. However, smartphones can simplify the process of gathering data and presenting information regarding the status of the orchard as it provides a middleman between the farmer and their *crops*. Smartphones are not only a powerful tool; they provide a sense of comfort in an intimidating field of technology to the farmers. Most of the farmers use smartphones in their everyday lives.

The benefit of integrating mobile applications as a means of orchard management is the accessibility farmers would have. Earlier methods discussed before such as sensors, machine vision, image processing, and machine learning lack the ability to share their respective tools. With mobile applications, there is a platform provided to obtain desired applications such as Apple's app store or Androids app store. There have been several applications that explore the ability to be used for agricultural purposes. Agricultural applications can be categorized into three groups (Mendes, et al., 2020):

A. Crop Operations

B. Farm Management

C. Information System

The scope of this project explores farm management applications as a means of precision agriculture.

Methods

The development of the Blossom Counting Application can be divided into the following steps:

1) Design of Experiment for image acquisition
2) Planning and Designing the front end of the mobile application
3) Development of the back end of the mobile application
4) Evaluation of application

Design of Experiment for image acquisition

The focus of this study is apple production. The site that was used for this study is an apple orchard managed by Symms Fruit Ranch (Figure 6). The apple orchard has the Pink Lady Variety. Twenty trees were selected from two rows. Two images of each tree from east and west were acquired using the iPad and iPhone. The iPad used in this study has an 8 MP camera while the iPhone has a 12 MP camera. Figure 7 and Figure 8 display Tree 19 from the east and west sides. The acquired images have a resolution of 2448×3264 pixels and were saved as jpg files.

Figure 6 - Symms Fruit Ranch

Figure 8 - Row 18 from East Side

Figure 7 - Row 18 from West Side

The platform selected to develop the Blossom Counting App was IOS. Then the user interface was designed in the Swift programming language, as this is the IOS programming language for application development. The back-end functionality was written in C++ and OpenCV, following the user interface. We then tested the application using the images acquired from the study site.

Planning and Designing the front end of the mobile application

When developing a mobile device application, consider two aspects: the front and back ends. The front end of a mobile application is responsible for displaying the information to the user and giving the feel of the application.

The development of the application takes place using the IOS platform. IOS language for designing a mobile application is Swift. When designing the user interface for the application, the intention was to keep it straightforward. The first portion of the front end was to establish what information needed to display. The user interface components can be seen in Figure 9 and Figure 10. Through the design process, the information chosen to be presented was:

1. the original image the user selected from either the camera or the photo library
2. the image processed through the back end
3. the value representing the number of blossoms detected
4. a button that allows the user to select a new image.

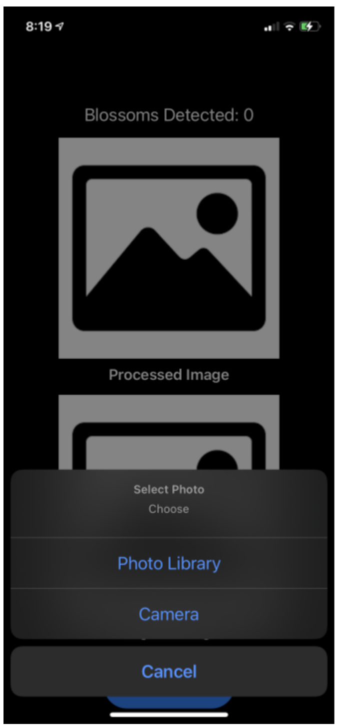

Figure 10 - Button Functionality

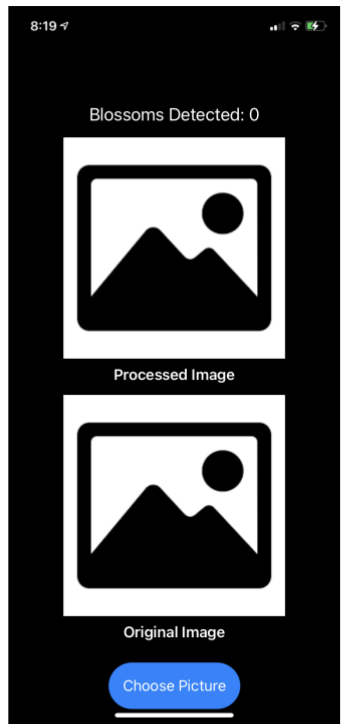

Figure 9 - Home Menu

Development of the Back End of the Mobile Device App

The back end of the mobile application is responsible for taking the data from the user and transforming it into the desired information. Development of the back-end function used an object-oriented language called C++ and a library called OpenCV, which is known for its image processing. The architecture of the overall application can be described as Model View Controller or MVC. Figure 11 shows how the data is moved within the application. Essentially this architecture is broken down into three pieces. First is the model, which is the data we pass into the application. Then the view can be described as the function of the front end, which is to display the information. The third is the Controller, which handles the data, where the back-end function lies. Since the application uses C++, a language unknown to Swift, a wrapper was required. The function of the wrapper is so the application can call functions that are foreign to the primary language, which is Swift.

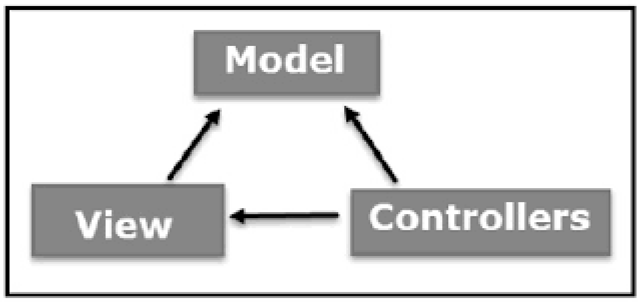

Figure 11 - MVC Architecture

This study builds on the image processing study conducted by previous members of the Robotics Vision (Bulanon et al., 2020). The first step in creating the back end is to read the image from the user. Swift stores its image as a UIImage while OpenCV handles image processing through matrix transformation. So a function had to be created to convert UIImage into a matrix. Following the conversion of the image, a color discriminant is placed upon the matrix to isolate the desired object. Essentially, the color discriminant targets pixels that fall within the discriminant. The condition used to analyze the pixel can be seen in Figure 12.

```
// Applying color filter to isolate blossoms.
for ( int row = 0; row < filterImage.rows; row++)
    for (int coll = 0; coll < filterImage.cols; coll++)
        if ((7 * filterImage.at<cv::Vec3b>(row,coll)[0] - 9 * filterImage.at<cv::Vec3b>(row,coll)[2] +
            135) && filterImage.at<cv::Vec3b>(row,coll)[2] < 155)
    {
        filterImage.at<cv::Vec3b>(row,coll) = cv::Vec3b(0,0,0);
    }
```

Figure 12 - Isolating Blossom Code Snippet

Applying the color discriminant results in an image that's been cropped, leaving only the blossoms that have been detected. The next step of the back-end functionality is to perform a blob analysis. Performing blob analysis will give us a value representing the number of blossoms the color discriminant detected. Figure 13 depicts a code snippet of how the blob analysis functions within the application.

```
std::vector<std::vector<cv::Point>> contours;
std::vector<cv::Vec4i> hierarchy;
cv::findContours(UnBinary, contours, hierarchy, cv::RETR_TREE, cv::CHAIN_APPROX_SIMPLE);

int BlossomsDetected = 0;

for (int pointer = 0; pointer < contours.size(); pointer++)
{
    if (cv::contourArea(contours[pointer]) > 50 && cv::contourArea(contours[pointer]) < 60)
    {
        BlossomsDetected = BlossomsDetected + 1;
    }
}
```

Figure 13 - Blob Analysis Code Snippet

Evaluation of Application

To test the accuracy of the application, we performed a correlation analysis between two data sets. The first is Blossom Detected by Application, and the second data set is Fruit Count. The first step was to manually count the fruits on the twenty selected trees throughout the agriculture season. We then used the application on the images gathered of the twenty trees recording how many blossoms were detected. Once the data sets of Blossom Detected and Fruit Count were organized, they were passed into Excel to perform the correlation analysis.

Discussion

Results

This project aims to develop a farmer-friendly mobile application to count the number of blossoms on a tree. A simple prototype was built through data acquisition and the development of the application itself. The back-end functionality can read in the original image and perform image processing to isolate the tree's blossoms. Figures 14, 15, and 16 shows the result of image processing. Figure 15 is the original image. Figure 14 is the result of applying the color discriminant function and then a size filter is then used to remove noise resulting in Figure 16.

Figure 15 – Original Image

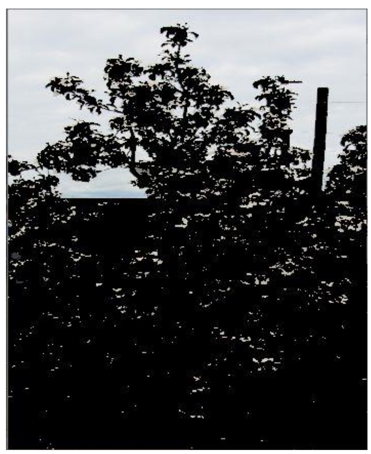

Figure 16 - Color Discriminant Image

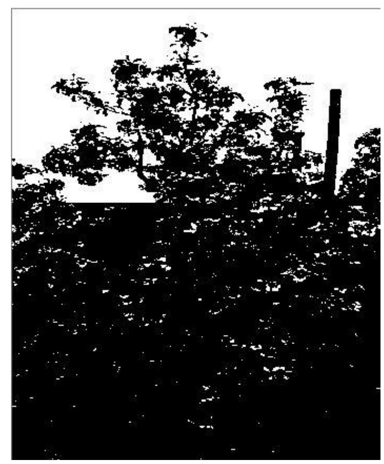

Figure 14 – Binary Image

From performing a correlation analysis between blossoms detected to the trees' manual fruit count, the results are 0.39 correlation seen in Figure 17. The results were not the ideal outcome of the prototype. However, what can be taken away from the outcome is that this is a positive correlation indicating that this method of counting blossoms can be improved in the future with more data and improving the application's functionality.

Tree #	Blossom Detected	Actual Fruit
1	91	14
2	108	84
3	159	32
4	168	59
5	104	80
6	150	84
7	165	121
8	153	63
9	135	64
10	161	146
Correlation: 0.39		

Figure 17 - Correlation Analysis Result

Challenges

The development of a farmer-friendly mobile application presented several challenges, such as:

1) OpenCV is a python library

2) Weather conditions

3) Color Discriminant

OpenCV is an image processing library from the language python. Some features that were offered in python are not offered in C++. As a result, functionalities of the image processing algorithms had to be manually developed. The language that provided the platform for the application was Swift because this is an IOS programming language for mobile applications. The application's front and back end were not written in the same languages, and a wrapper was required to co-exist.

The color discriminant used for the application was created from 2017 images.

This project explored the concept of using a color discriminant for yearly uses. The issue with using a color discriminant year to year is the changing factors these crops undergo annually. Some factors need to be considered. However, factors such as weather changes or the process of thinning crops are too unpredictable to consider.

Future Work

For the Blossom Detection Application to be a working tool within orchards, areas of improvement can be made. The user interface is simple and provides the necessary information for counting blossoms. However, there is no option for farmers to save their data. Adding a database to the application would be a priority for this project to ensure data is being collected properly.

As discussed in this section's challenge portion, a color discriminant is not an ideal solution for detecting blossoms within an image. Two approaches should be considered when detecting blossoms. First, use Apple's image processing library rather than using a foreign language and library for image processing algorithms. Apple recently developed an image processing library called 'Core Image', which has similar features to OpenCV. A second approach for blossom detection is machine learning. The main problem with the color discriminant is the changing factors to consider. With sufficient data, machine learning can consider multiple factors and accurately detect blossoms.

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